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Effects of product replacement programs on climate change

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ABSTRACT

Product replacement programs promote the replacement of durable goods such as automobiles, home appliances and houses with new energy-efficient products using financial incentives such as subsidies. Many countries have implemented such programs to reduce environmental loads. These programs affect the point in time at which the decision to replace a product is made (and acted on) by consumers, which, in turn, influences the overall effectiveness of the program. Thus, in order to improve the policy design of these replacement programs, it is necessary to consider the mechanism of the consumer product replacement decision. This study examines the effects of the Japanese Home Appliance Eco-Point Program on the timing of household air conditioner replacements and the resulting GHG emission reduction effects and assesses the program's cost-effectiveness using a dynamic discrete choice model and an input–output model. We found that the program increased the air conditioner replacement rate by 1.5%–1.9% and reduced GHG emissions by 28,516 tCO_2eq. However, the cost per ton of CO_2eq reduced was approximately 978 US dollars, which is quite high compared to the GHG emission reduction costs of other programs. We conclude that the Home Appliance Eco-Point Program as constituted in 2009–2010 was not a cost-effective means to reduce GHG emissions and that appropriate policy coordination needs to be conducted in order to improve the cost-effectiveness of such programs in the future.

1. Introduction

Product replacement programs (accelerated replacement programs) that encourage consumers to replace older products with new energy-efficient products have been implemented in a number of countries. To promote replacement demand, subsidies and tax reductions are typically offered. Although these programs act as an economic stimulus by increasing the demand for replacements, their primary aim is environmental: reducing the environmental load that results from the use of consumer durables. In order to properly assess the performance of a product replacement program, it is crucial to determine the extent to which the program increases demand for replacements and the extent to which environmental loads are reduced.

A number of studies have made quantitative assessments of product replacement programs (e.g., Lenski et al., 2010, 2013; Yoshida et al., 2010; Kagawa et al., 2013; Li et al., 2013; Datta and Gulati, 2014; Davis et al., 2014; Antweiler and Gulati, 2015; Morita and Arimura, 2016; DeShazo et al., 2017; Nakano and Washizu, 2017). For example, Li et al. (2013), using difference-in-differences regression, analyzed the influence on auto sales and CO_2 emissions exerted by the "Cash for Clunkers" program, a short-term product replacement program for passenger cars conducted in the U.S. in 2009. The program's cost-effectiveness was also assessed. In general, product replacement programs have an effect on the point in time at which consumers choose to replace an older product through a replacement decision mechanism. This ultimately influences the effectiveness of the program since changes in the point in time of product replacement affect the composition of the overall array of energy-consuming products in use (i.e., how many products from each production year are being used), which, in turn, affects the amount of energy consumed in product usage. In assessing any product replacement program, it would seem essential that due consideration be given to the structure of this mechanism. In particular, it is important to analyze how replacement decisions would change if the program had not been implemented. However, no previous studies have explicitly identified and analyzed the mechanism driving consumer replacement decisions in order to assess the effectiveness of a replacement program.

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In related research, earlier studies (e.g., Cooper, 2004; Nes and Crammer, 2005; Cox et al., 2013) have used questionnaire surveys to establish the various factors influencing product disposal decisions. For instance, Cooper (2004) classified the reasons why consumers decide to dispose of certain consumer durables into (1) absolute obsolescence attributable to physical product failure and (2) relative obsolescence attributable to a decision made by the consumer prior to the failure of the product. Cooper (2004) further divided relative obsolescence into three sub-categories: "psychological obsolescence," whereby consumers are no longer fascinated by the product; "economic obsolescence," whereby the product is not worth keeping economically; and "technical obsolescence," whereby consumers are attracted to the improved functions and performance of the new products. Factors obstructing the replacement of older products with energy-efficient products have also been examined (e.g., Jaffe and Stavins, 1994; Brown, 2001; Sorrell et al., 2004; Gillingham et al., 2009). Sorrell et al. (2004) listed 15 concrete "barriers to energy efficiency" from economic, behavioral, and organizational theory perspectives and discussed countermeasures for removing each barrier (see Table 2.3 in Sorrell et al. (2004)). While such studies have qualitatively considered factors influencing product replacement, none quantitatively analyze the effects of these factors on the consumer replacement decision.

In the field of economics, significant attention has been given to the development of a dynamic discrete choice model (e.g., Rust, 1987; Schiraldi, 2011; Rapson, 2014). Such a model was originally proposed by Rust (1987). In a dynamic discrete choice model, as applied to product replacement, it is basically assumed that a consumer has a sense of the expected value of keeping his/her product (i.e., not replacing) and the expected value of replacing it, and that he/she decides to keep or replace the product by comparing these expected values. The model proposed here models the consumer's situation by combining a discrete choice model with the Bellman equation, which makes possible a quantitative analysis of how each factor (e.g., replacement cost, energy efficiency of a particular product) affects the replacement probabilities for a particular product.

Based on the above motivation, we quantitatively assess the influence of a product replacement program on the replacement point of consumers and on the environment, and examine the effectiveness of a product replacement program as environmental policy using a dynamic discrete choice model. Focusing on Japan's Home Appliance Eco-Point Program and looking specifically at household air conditioners, this study clarifies the GHG emissions reduction effects resulting from the promotion of household air conditioner replacement and evaluates the cost-effectiveness of the program as a policy for reducing GHG emissions. Based on results, we discuss future measures for more effective emissions reduction.

2. Methods and data

2.1. Model

2.1.1. Overview of the home appliance eco-point program in Japan

The Home Appliance Eco-Point Program was a product replacement program implemented in Japan from May 2009 through March 2011, targeting televisions, air conditioners, and refrigerators. Under this program, if a consumer purchased a product meeting certain energy performance criteria, then the consumer earned a designated number of "eco-points." Each eco-point was equivalent to 1 Japanese yen (JPY) and was exchangeable for such items as a gift voucher. Thus, the Home Appliance Eco-Point Program provided economic incentives for replacing a product with one having superior energy efficiency. The total number of issued eco-points earned by individuals was approximately 45 million, of which televisions accounted for the majority (72.09%), followed by air conditioners (16.28%) and refrigerators (11.63%) (Ministry of the Environment of Japan, 2012b). Notably, the number of eco-points issued for televisions was almost certainly higher because the program was implemented at a time when consumers were already switching to televisions capable of accommodating terrestrial digital media broadcasting. If televisions are excluded from the total, the number of eco-points issued for air conditioners, the target product of this study, would be highest. It can be said, then, that from an eco-point issuance perspective, the Home Appliance Eco-Point Program exerted considerable influence on air conditioner replacement. This study specifically analyzes the replacement of household air conditioners produced from 1995 to 1999 and replaced between 2005 and 2013. (This somewhat narrower focus is due to certain data availability and data consistency limitations.)

2.1.2. Dynamic discrete choice model for air conditioner replacement decisions

In our analysis, we consider the replacement problem to be a dynamic infinite-horizon discrete choice problem in which a consumer decides to replace a certain vintage of air conditioner. Specifically, in each year t, a consumer with an air conditioner produced in year i decides whether to keep the old model air conditioner or replace it with a new one. The consumer makes the year t replacement decision based on the following factors: $e_{i,t}$, the energy efficiency (annual electricity consumption) in year t of an air conditioner produced in year i; e_t^{new}, the energy efficiency of a new air conditioner produced and sold in year t; p_t^{ac}, the price of a new air conditioner sold in year t; and p_t^{ep}, the monetary value of the eco-points awarded through the Home Appliance Eco-Point Program in year t. We assume that the consumer has and understands information related to these factors in year t. It is also noteworthy that $t \geq i$.

We express the consumer's replacement decision at year t as a binary variable, $a_{i,t}$, where $a_{i,t} = 0$ signifies that the consumer makes no replacement at year t and $a_{i,t} = 1$ signifies that the consumer replaces an owned product with a new one. Consumer utility at year t can be formulated for each replacement decision as follows:

$$u_{i,t} = u_{i,t}(e_t^{new}, p_t^{ac}, a_{i,t}) = \begin{cases} \alpha_0 + \alpha_1 (e_{i,t} - e_t^{new}) p_t^e & \text{if } \ a_{i,t} = 0 \\ \alpha_2 (p_t^{ac} - p_t^{ep}) & \text{if } \ a_{i,t} = 1 \end{cases} \tag{1}$$

Here, α_0, α_1, and α_2 are the parameters; p_t^e represents the price of electricity per unit in year t. It is noteworthy that the utility obtained from the action of keeping one's old air conditioner is affected by the *avoidable* electricity cost calculated as $(e_{i,t} - e_t^{new})p_t^e$, whereas the consumer utility obtained from replacement with a new air conditioner is affected by the net price of the new air conditioner, which considers the monetized eco-points, p_t^{ep}, and is calculated as $p_t^{ac} - p_t^{ep}$. Both α_1 and α_2 are likely to be negative because a higher avoidable electricity cost can be a strong incentive to replace an older-model air conditioner with a new air conditioner, whereas a higher net price of a new air conditioner can be a strong incentive to continue using an older-model air conditioner. We assumed that the consumer does not consider maintenance and disposal costs when making a replacement decision in year t and that the consumer does not buy a second-hand air conditioner.

Based on the utility function in Eq. (1), a consumer determines his/her replacement decision policy, expressed as $\pi = \{a_{i,t}, a_{i,t+1}, a_{i,t+2}, \cdots\}$, to maximize the expected sum of current and discounted

future utility according to the value function defined as follows:

$$V(e_t^{new}, p_t^{ac}) = \max_{\pi} E_{e^{new}, p^{ac}}\left[\sum_{\tau=t}^{\infty} \beta^{s-t} u_{i,\tau}(e_\tau^{new}, p_\tau^{ac}, a_{i,\tau})\right] \tag{2}$$

In this equation, β is a discount factor ($0 \le \beta < 1$). For this study, we set the discount factor as 0.9, similar to earlier studies (Schiraldi, 2011; Rapson, 2014). A unique solution of the value function in Eq. (2) is obtainable using Bellman's equation, as follows (Rust, 1987; Rapson, 2014):

$$\begin{aligned} V\left(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}\right) &= \max_{a_{i,t}=0,1}\left\{V\left(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t}\right)\right\} \\ &= \max_{a_{i,t}=0,1}\left\{u_{i,t}(e_t^{new}, p_t^{ac}, a_{i,t}) + \varepsilon_{i,t,a_{i,t}} \right. \\ &\quad \left. + \beta EV\left(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t}\right)\right\} \end{aligned} \tag{3}$$

Here, $V(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t})$ in the second row is a choice-specific value function, where $\varepsilon_{i,t,a_{i,t}}$ is an unobservable error term. Assuming that the energy efficiency and the unit price of a new air conditioner, e_t^{new} and p_t^{ac}, follow a first-order Markov probabilistic process (Rapson, 2014), the expected value in the third row of Eq. (3), $EV(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t})$, can be expressed as

$$\begin{aligned} EV\left(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t}\right) = &\int_{\tilde{e}^{new}}\int_{\tilde{p}^{ac}}\int_{\tilde{\varepsilon}_i} V(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{\varepsilon}_i) \\ &f\left(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{\varepsilon}_i \middle| e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t}\right) \\ &d\tilde{e}^{new} d\tilde{p}^{ac} d\tilde{\varepsilon}_i \end{aligned} \tag{4}$$

In this equation, $f(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{\varepsilon}_i | e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t})$ is the conditional joint transition probability density function of e_t^{new}, p_t^{ac}, and $\varepsilon_{i,t}$. We assume *conditional independence* among these three random variables following Rust (1987). This enables us to infer the following functional relationship regarding the joint transition probability function: $f(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{\varepsilon}_i | e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t}) = g_1(\tilde{\varepsilon}_i | \tilde{e}^{new}, \tilde{p}^{ac}, \varepsilon_{i,t,a_{i,t}}) g_2(\tilde{e}^{new} | e_t^{new}, a_{i,t}) g_3(\tilde{p}^{ac} | p_t^{ac}, a_{i,t})$. Thus, we can rewrite the expected value described in Eq. (4) as

$$\begin{aligned} EV\left(e_t^{new}, p_t^{ac}, \varepsilon_{i,t,a_{i,t}}, a_{i,t}\right) &= \int_{\tilde{e}^{new}}\int_{\tilde{p}^{ac}}\int_{\tilde{\varepsilon}_i} V(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{\varepsilon}_i) g_1\left(\tilde{\varepsilon}_i \middle| \tilde{e}^{new}, \tilde{p}^{ac}, \varepsilon_{i,t,a_{i,t}}\right) g_2(\tilde{e}^{new} | e_t^{new}, a_{i,t}) g_3(\tilde{p}^{ac} | p_t^{ac}, a_{i,t}) d\tilde{e}^{new} d\tilde{p}^{ac} d\tilde{\varepsilon}_i \\ &= \int_{\tilde{e}^{new}}\int_{\tilde{p}^{ac}}\left[\int_{\tilde{\varepsilon}_i} V(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{\varepsilon}_i) g_1\left(\tilde{\varepsilon}_i \middle| \tilde{e}^{new}, \tilde{p}^{ac}, \varepsilon_{i,t,a_{i,t}}\right) d\tilde{\varepsilon}_i\right] g_2(\tilde{e}^{new} | e_t^{new}, a_{i,t}) g_3(\tilde{p}^{ac} | p_t^{ac}, a_{i,t}) d\tilde{e}^{new} d\tilde{p}^{ac} \end{aligned} \tag{5}$$

Moreover, we make the additional assumption that error term $\varepsilon_{i,t,a_{i,t}}$ follows an independent and identically distributed Type I extreme-value distribution function. Consequently, we can express the expected value in Eq. (5) in logsum form (Small and Rosen, 1981; Rust, 1987):

$$\begin{aligned} EV(e_t^{new}, p_t^{ac}, a_{i,t}) = &\int_{\tilde{e}^{new}}\int_{\tilde{p}^{ac}} \log\left[\sum_{\tilde{a}_{i,t}=0,1} \exp\{V(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{a}_{i,t})\}\right] \\ &\times g_2(\tilde{e}^{new} | e_t^{new}, a_{i,t}) g_3(\tilde{p}^{ac} | p_t^{ac}, a_{i,t}) d\tilde{e}^{new} d\tilde{p}^{ac} \\ = &\int_{\tilde{e}^{new}}\int_{\tilde{p}^{ac}} \log\left[\sum_{\tilde{a}_{i,t}=0,1} \exp\{u_{i,t}(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{a}_{i,t}) \right. \\ &\left. + \beta EV(\tilde{e}^{new}, \tilde{p}^{ac}, \tilde{a}_{i,t})\}\right] \\ &\times g_2(\tilde{e}^{new} | e_t^{new}, a_{i,t}) g_3(\tilde{p}^{ac} | p_t^{ac}, a_{i,t}) d\tilde{e}^{new} d\tilde{p}^{ac} \end{aligned} \tag{6}$$

To obtain the expected value in Eq. (6), we set the discretized transition probabilities of the two state variables, e_t^{new} and p_t^{ac}. Following Tauchen (1986), we conducted first-order autoregression analyses for energy efficiency and the price of a new air conditioner as follows (Schiraldi, 2011; Rapson, 2014):

$$\log(e_{t+1}^{new}) = b_0 + b_1 \log(e_t^{new}) + \eta_t \ \eta_t \sim N\left(0, \sigma_e^2\right) \tag{7}$$

$$\log(p_{t+1}^{ac}) = c_0 + c_1 \log(p_t^{ac}) + \rho_t \ \rho_t \sim N\left(0, \sigma_a^2\right) \tag{8}$$

Here, η_t and ρ_t respectively represent the unobserved error terms of energy efficiency and price. Using parameters b_0, b_1, c_0, and c_1 and the standard deviations of the residuals related to the two error terms obtained from the autoregression analyses, we calculated the *discretized* transition probabilities of each bin of the two state variables, e_t^{new} and p_t^{ac}, expressed respectively as $P(\tilde{e}_r^{new} | e_t^{new}, a_{i,t})$ and $P(\tilde{p}_s^{ac} | p_t^{ac}, a_{i,t})$, where r and s represent the grid numbers of the bins of each state variable. Tauchen (1986) provides details for estimating the transition probabilities. Detailed Markov transition probability results for the state variables are given in Supporting Information.

Substituting the two discretized Markov transition probabilities obtained from the above method, $P(\tilde{e}_r^{new} | e_t^{new}, a_{i,t})$ and $P(\tilde{p}_s^{ac} | p_t^{ac}, a_{i,t})$, for the transition probabilities $g_2(\tilde{e}^{new} | e_t^{new}, a_{i,t})$ and $g_3(\tilde{p}^{ac} | p_t^{ac}, a_{i,t})$, we can rewrite the expected value in Eq. (6) as

$$EV\left(e_t^{new}, p_t^{ac}, a_{i,t}\right) = \sum_{r=1}^{R}\sum_{s=1}^{S} P\left(\tilde{e}_r^{new}\middle|e_t^{new}, a_{i,t}\right)P\left(\tilde{p}_s^{ac}\middle|p_t^{ac}, a_{i,t}\right) \log\left[\sum_{\tilde{a}_{i,t}=0,1} \exp\left\{u\left(\tilde{e}_r^{new}, \tilde{p}_s^{ac}, \tilde{a}_{i,t}\right) + \beta EV\left(\tilde{e}_r^{new}, \tilde{p}_s^{ac}, \tilde{a}_{i,t}\right)\right\}\right] \tag{9}$$

In this equation, R and S respectively denote the grid size of the discretized values for the energy efficiency and unit price of a new air conditioner. We set the grid size to 30, meaning we considered a 30×30 state space for the state variables e_t^{new} and p_t^{ac}. The results of parameter estimation for other state space sizes and a discussion of those results are shown in Supporting Information.

Using the expected value form in Eq. (9), we can compute EV as a fixed point of a contraction mapping (Rust, 1987):

$$EV^q\left(e_t^{new}, p_t^{ac}, a_{i,t}\right) = \sum_{r=1}^{R}\sum_{s=1}^{S} P\left(e_{t+1,r}^{new}\middle|e_t^{new}\right)P\left(p_{t+1,s}^{ac}\middle|p_t^{ac}\right) \log\left[\sum_{a_{i,t+1}=0,1} \exp\left\{u_{i,t+1}\left(e_{t+1,r}^{new}, p_{t+1,s}^{ac}, a_{i,t+1}\right) + \beta EV^{q-1}\left(e_t^{new}, p_t^{ac}, a_{i,t}\right)\right\}\right] \tag{10}$$

where q represents the number of iterations of the contraction mapping. In this study, we found the fixed point of the expected value using Eq. (10) with the convergence criterion $\|EV^q - EV^{q-1}\| < 10^{-5}$.

Using the expected value, $EV(e_t^{new}, p_t^{ac}, a_{i,t})$, obtained from Eq. (10), the assumption that $\varepsilon_{i,t,a_{i,t}}$ independently and identically follows a Type I extreme-value distribution yields the probability of replacement, $P(a_{i,t} = 1)$, and the probability of keeping one's current air conditioner, $P(a_{i,t} = 0)$, according to the logit following choice probabilities:

$$\begin{cases} P(a_{i,t}=1) = \dfrac{\exp\left\{u_{i,t}\left(e_t^{new}, p_t^{ac}, a_{i,t}=1\right) + \beta EV\left(e_t^{new}, p_t^{ac}, a_{i,t}=1\right)\right\}}{\sum\limits_{\tilde{a}_{i,t}=0,1} \exp\left\{u_{i,t}\left(e_t^{new}, p_t^{ac}, \tilde{a}_{i,t}\right) + \beta EV\left(e_t^{new}, p_t^{ac}, \tilde{a}_{i,t}\right)\right\}} \\ P(a_{i,t}=0) = 1 - P(a_{i,t}=1) \end{cases} \tag{11}$$

According to the dynamic discrete choice model in Eq. (11), each consumer chooses whether to keep or replace an old-model air conditioner by considering two future state variables: the energy efficiency, e_t^{new}, and price of a new air conditioner, p_t^{ac}.

We used maximum likelihood estimation to obtain the parameters of the dynamic discrete choice model, α_0, α_1, and α_2, and the following as the log-likelihood function:

$$\log L = \sum_i \sum_t w_{i,t} \log\left(\tilde{P}_{i,t}\right) \tag{12}$$

In this equation,

$$\tilde{P}_{i,t} = \prod_{l=i+1}^{t-1} \{P(a_{i,l} = 0)\} \times P(a_{i,t} = 1) \tag{13}$$

and $w_{i,t}$ is the number of air conditioners produced in year i and replaced in year t. Parameters α_0, α_1, and α_2 were chosen to maximize the log-likelihood function in Eq. (12). The criterion value of the maximum likelihood estimation was set to 10^{-6}; that is, the criterion of the maximum likelihood estimation was $\|\log L_\theta - \log L_{\theta-1}\| < 10^{-6}$, where θ is a subscript indicating the iteration of the maximum likelihood method. The initial value of each parameter was set to -1. We tested the significance of the parameters using the bootstrap method with the number of bootstrap replications equal to 100. Details of the bootstrap method are provided in the Data section.

2.1.3. *Estimating the effects of the home appliance eco-point program on GHG emissions*

We estimated the effects of the Home Appliance Eco-Point Program on GHG emissions by combining the dynamic discrete choice model and an input–output framework (Miller and Blair, 2009). Based on the estimated parameters of the discrete choice model, we can calculate the number of air conditioner replacements and the amount of electricity use each year, both with the home appliance eco-point program (baseline) and without the program; the number of eco-points awarded to consumers who replace their air conditioners under the program can also be calculated. Setting the monetary value of the eco-points awarded, p_t^{ep} in Eq. (1), equal to zero enables us to estimate the replacement probabilities in year t if the Home Appliance Eco-Point Program had not been implemented (that is, *without* the program). We express the probabilities as $\tilde{P}_{i,t}^{Without} = \prod_{l=i+1}^{t-1}\{P(a_{i,l} = 0|p_t^{ep} = 0)\} \times P(a_{i,t} = 1|p_t^{ep} = 0)$. Similarly, we express the replacement probability in year t *with* the program as $\tilde{P}_{i,t}^{With} = \prod_{l=i+1}^{t-1}\{P(a_{i,l} = 0)\} \times P(a_{i,t} = 1)$. Thus, the change in product replacement probability attributable to the eco-point program, $\Delta\tilde{P}_{i,t}$, is simply $\Delta\tilde{P}_{i,t} = \tilde{P}_{i,t}^{With} - \tilde{P}_{i,t}^{Without}$.

When analyzing the impact of the Home Appliance Eco-Point Program on GHG emissions, we consider the following two effects: (1) the *eco-point use effect*, which is the effect of increased final demand stimulated by the eco-points awarded through the program; and (2) the *electricity use decrease effect*, which is the effect of decreasing the electricity use of air conditioners due to the replacement of older air conditioners with more energy-efficient units stimulated by the program.

If the number of purchased household air conditioners from production year i is N_i, then the effect of the Home Appliance Eco-Point Program on the replacement of air conditioners in year t can be formulated as $\Delta h_t^{ac} = \sum_i \Delta\tilde{P}_{i,t} \times N_i$. The value of the eco-points awarded for air conditioner replacement, expressed as ep, is calculable by multiplying Δh_t^{ac}, the number of extra new household air conditioners purchased in year t because of the program, by the monetized per-replacement eco-points awarded in year t; that is, $ep = \sum_t \Delta h_t^{ac} \times p_t^{ep}$. Assuming that consumers

spend their earned eco-points following their usual pattern of spending on final goods, the increase in final demand for products from industrial sector j induced by these points is calculable as

$$\Delta f_k^{epuse} = \frac{f_k}{\sum_{j=1}^{J} f_j} \times ep \tag{14}$$

In this equation, f_k signifies the final demand for products from industrial sector k in the household sector obtained from the input–output table; J indicates the number of industrial sectors in the input–output table. The points awarded through the Home Appliance Eco-Point Program are mainly exchanged for product vouchers. Therefore, in calculating Δf_k^{epuse} in Eq. (14), the value of f_k is set to zero for the household air conditioner sector (the object product of the Home Appliance Eco-Point Program) and all industrial sectors from which products cannot be purchased with a voucher (Electricity, Gas supply, Steam and hot water supply, Water supply, Sewage disposal, Waste management service, Financial service, Life insurance, Non-life insurance, Real estate agency and manager, Real estate rental service, House rent, Public administration, School education, Social education, Miscellaneous educational and training institutions, Medical service, Health and hygiene, Social insurance, Social wealth, and Nursing care). Using the calculated increase in household final demand for sector k products attributable to the program, Δf_k^{epuse}, we can estimate the change in GHG emissions associated with *eco-point use effect* using the input–output model

$$\Delta G^{epuse} = \mathbf{g}' \Delta \mathbf{f}^{epuse} = \begin{bmatrix} g_1 & \cdots & g_J \end{bmatrix} \begin{bmatrix} \Delta f_1^{epuse} \\ \vdots \\ \Delta f_J^{epuse} \end{bmatrix} \tag{15}$$

Here, $\mathbf{g}'$ is a row vector of embodied GHG emission coefficients, with elements $(g_1, \cdots, g_J)$ respectively representing the volume of GHG emissions per unit of production in each sector.

The diffusion of new energy-efficient air conditioners stimulated by the Home Appliance Eco-Point Program contributed to reducing household electricity demand and GHG emissions. By using the replacement probabilities estimated from the discrete choice model, $\tilde{P}_{i,t}^{With}$, the number of purchased household air conditioners from production year i, N_i, and the energy efficiency of the new and owned air conditioners, e_t^{new} and $e_{i,t}$, we are able to estimate the total electricity consumption from the use of air conditioners in year t as

$$E_t^{with} = \underbrace{\sum_i \left\{ N_i \times \left(1 - \sum_{v=i+1}^{t} \tilde{P}_{i,v}^{with} \right) \times e_{i,t} \right\}}_{\substack{\text{Electricity consumptio} \\ \text{using } \textit{owned} \text{ air conditioners}}} + \underbrace{\sum_i \sum_{t'=i}^{t} \left\{ N_i \times \tilde{P}_{i,t'}^{with} \times e_{t'}^{new} \right\}}_{\substack{\text{Electricity consumption} \\ \text{using } \textit{replaced} \text{ air conditioners}}} \tag{16}$$

In Eq. (16), the $(1 - \sum_{v=i+1}^{t} \tilde{P}_{i,v}^{with})$ term in the first expression represents the cumulative survival probability in year t of owned air conditioners produced in year i. As a whole, the first expression in Eq. (16) represents the electricity consumption from the use of owned air conditioners in year t assuming that the Home Appliance Eco-Point Program is implemented. The second expression in Eq. (16) represents the electricity consumption of the replacement air conditioners in year t under the same assumption (i.e., the Eco-Point Program is implemented). We assumed that once the air conditioners are replaced with new units, the new units are used until 2013.

Similarly, the total electricity consumption using air conditioners for the case in which the Home Appliance Eco-Point Program is *not* implemented is

$$E_t^{without} = \underbrace{\sum_i \left\{ N_i \times \left(1 - \sum_{v=i+1}^{t} \tilde{P}_{i,v}^{without} \right) \times e_{i,t} \right\}}_{\substack{\text{Electricity consumption} \\ \text{using } \textit{owned} \text{ air conditioners}}} + \underbrace{\sum_i \sum_{t'=i}^{t} \left\{ N_i \times \tilde{P}_{i,t'}^{without} \times e_{t'}^{new} \right\}}_{\substack{\text{Electricity consumption} \\ \text{using } \textit{replaced} \text{ air conditioners}}} \tag{17}$$

Based on Eqs. (16) and (17), the change in GHG emissions attributable to the *electricity use decrease effect* is calculable as

$$\Delta G^e = \sum_t \left(E_t^{with} - E_t^{without} \right) \times g_e \tag{18}$$

Here, g_e is the embodied GHG emission coefficient per physical unit of electricity.

Adding ΔG^{epuse} in Eq. (15) and ΔG^e in Eq. (18), we can ascertain the effect of the Home Appliance Eco-Point Program on GHG emissions:

$$\Delta G^{ep} = \Delta G^{epuse} + \Delta G^e \tag{19}$$

Because use of the earned eco-points can be expected to increase final demand for goods other than household air conditioners, the *eco-point use effect* on GHG emissions, ΔG^{epuse} in Eq. (19), will add to the emissions total, offsetting to some extent the *electricity consumption decrease effect* on GHG emissions, ΔG^e in Eq. (19).

2.2. Data

The data used to produce the sample for our maximum likelihood estimation, $w_{i,t}$, were from the "Research report on the elapsed years of four types of discarded home appliances" series for the period 2005–2013 provided by the Association for Electric Home Appliances in Japan (AEHA) (AEHA, 2006 through 2014). The reports show the number of end-of-life home appliances for the various production years as detected at collection facilities designated by the Home Appliance Recycling Law in Japan. We used the numbers of end-of-life air conditioners from production years $i = 1995, 1996, 1997, 1998, 1999$ that were observed in years $t = 2005, 2006, \ldots, 2013$ as the sample in our parameter estimation. It should be noted that the sample size in the report for 2011 (i.e., $\sum_i w_{i,2011}$) is roughly 12% larger than the average of the sample sizes in the other years. To avoid the distortion in parameter estimation that this might create, for the 2011 sample, we calculated the ratio of the sample size for each production year to the total sample size, and then adjusted the 2011 sample size for each production year by multiplying the calculated ratios by the average of the total sample size for all years other than 2011.

As to the bootstrap method, we generated a bootstrap sample by observation year (t = 2005, 2006, …, 2013) from the data and conducted our parameter estimation using the number of end-of-life air conditioners from the various production years (i = 1995, 1996, 1997, 1998, 1999) obtained from the sample. We

repeated this procedure 100 times. In generating the bootstrap sample, we calculated the ratios of the sample size of each production year for each observation year, and then generated the bootstrap sample using the calculated ratios as weights for the bootstrap re-sampling.

To establish the energy efficiency (annual electricity consumption) of air conditioners produced between 1995 and 2013, we used data from the "Energy-saving performance catalog" provided by the Agency for Natural Resources and Energy of Japan (Agency for Natural Resources and Energy of Japan, 2010 through 2014). The catalog shows the "average" annual electricity consumption of a 2.8 kW class air conditioner by production year. However, the catalog-based annual electricity consumption is known not to be the actual amount. According to a report by the National Institute of Advanced Industrial Science and Technology of Japan (2010), the actual annual electricity consumption per household is only 18% of the catalog-based annual electricity consumption amount (National Institute of Advanced Industrial Science and Technology of Japan, 2010). We therefore multiplied the catalog-based annual electricity consumption by 18% and used the resulting values for $e_{i,t}$ and e_t^{new}. Given the unavailability of data regarding the efficiency-related deterioration rates of air conditioners due to aging, we applied an annual deterioration rate of 1%, as did Rapson (2014).

As to the price of a new air conditioner, p_t^{ac}, we used the average unit price of an air conditioner in each year t calculated from physical and monetary annual shipment data provided by the Japan Refrigeration and Air Conditioning Industry Association (Japan Refrigeration and Air Conditioning Industry Association (JRAIA)). For the unit price of electricity, p_t^e, we used the average unit price of electricity in each year t calculated from physical and monetary annual sales of lighting provided by the Federation of Electric Power Companies of Japan (Federation of Electric Power Companies of Japan).

The number of eco-points awarded for unit replacement under the Home Appliance Eco-Point Program changed several times during the course of the program. If a consumer replaced an old-model air conditioner with a new 2.8 kW class air conditioner from May 2009 through November 2010, the consumer was awarded 10,000 points, whereas 7000 points were awarded if the unit was purchased in December 2010. Only 4000 points were given for purchases made from January 2011 through March 2011 (Ministry of the Environment of Japan, Ministry of Economy, Trade and Industry of Japan, Ministry of Internal Affairs and Communications of Japan). One eco-point had the value of 1 JPY (Ministry of the Environment of Japan, 2012a). Correspondingly, we set $p_{2009}^{ep} = 10,000$ and $p_{2010}^{ep} = 4,000$ for the points awarded respectively in 2009 and 2010, and $p_t^{ep} = 0$ for the other years in the study. The prices of electricity and air conditioners, p_t^e and p_t^{ac}, were normalized by the consumer price indices (CPI) of the respective goods. The monetary eco-points, p_t^{ep}, were normalized by the consumer price index (CPI) of all goods. In each case, we used the consumer price index (CPI) normalized to 2015 as provided by the Statistical Bureau of Japan (2017).

The expected value $EV(e_t^{new}, p_t^{ac}, a_{i,t})$ in Eq. (10) diverges on running the program code with MATLAB if the values of the variables in Eq. (1) are large, making it impossible to estimate the discrete choice model. Consequently, we converted the units of p_t^{ac} and p_t^{ep} to 10,000 JPY, the units of $e_{i,t}$ and e_t^{new} to 100 kWh, and the unit of p_t^e to 100 JPY/100 kWh.

To match the period during which the sample was observed, N_i (the number of household air conditioners sold in the various production years used to estimate the GHG emissions reduction attributable to the Home Appliance Eco-Point Program as described in Section 2.3) must be adjusted for the number of household air conditioners purchased for replacement during the study period from 2005 to 2013. Using the product lifetime distribution of household air conditioners provided by the Ministry of the Environment of Japan (2011), we estimated the number of household air conditioners sold in production years 1995 through 1999 as $N_{1995} = 2,878,970$, $N_{1996} = 3,147,323$, $N_{1997} = 2,840,570$, $N_{1998} = 2,803,288$, and $N_{1999} = 2,807,258$. Thus, we specifically examined 14,477,409 units of air conditioners sold during this five-year period.

Similarly, the replacement rates with and without the Home Appliance Eco-Point Program (i.e., $\tilde{P}_{i,t}^{With}$ and $\tilde{P}_{i,t}^{Without}$) must be adjusted to the replacement rate over the study period. To estimate the GHG emission reduction attributable to the Home Appliance Eco-Point Program as described in Section 2.3, we used $\tilde{P}_{i,t}^{With*}$ and $\tilde{P}_{i,t}^{Without*}$ as the scaled replacement rates calculated by substituting $\tilde{P}_{i,t}^{With}$ and $\tilde{P}_{i,t}^{Without}$ into the following:

$$\tilde{P}_{i,t}^{With*} = \frac{\tilde{P}_{i,t}^{With}}{\sum_{m=2005}^{2013} \tilde{P}_{m,t}^{With}} \tag{20}$$

$$\tilde{P}_{i,t}^{Without*} = \frac{\tilde{P}_{i,t}^{Without}}{\sum_{m=2005}^{2013} \tilde{P}_{m,t}^{Without}} \tag{21}$$

To calculate the increase in final demand for products from each sector associated with the use of earned eco-points, Δf_k^{epuse} in Eq. (14), we used the 2011 Japanese Input–Output Table (395 sectors) (Ministry of Internal affairs and Communications of Communications Japan, 2015), which gives data for approximately those years during which the Home Appliance Eco-Point Program was in force.

For the embodied GHG emission coefficient $\mathbf{g}'$, we used the $(\mathbf{I} - \mathbf{A})^{-1}$-type (imports are not excluded) embodied GHG emission coefficients per monetary unit of production for each industrial sector in Japan, based on the 2011 Japanese domestic input–output table obtained from the "Embodied energy and emission intensity data for Japan using input–output tables (3EID)" (Nansai, 2018). We also calculated the embodied GHG emission coefficient per physical unit of electricity, g_e, based on the above GHG emission coefficient data per monetary unit of electricity consumption and the total physical and monetary output obtained from the 2011 Japanese Input–Output Table (Ministry of Internal affairs and Communications of Communications Japan, 2015).

2.3. Limitations

The increased replacement demand for air conditioners induced by the eco-point program would surely cause GHG emissions increases in both the unit production and disposal phases. According to Nakamura and Kondo (2006), however, most of the life-cycle GHG emissions of air conditioners are derived from the use phase, while GHG emissions from the production and disposal phases are marginal. Therefore, for calculation simplicity, the present study does not include these GHG emissions increases in analyzing the impact of the eco-point program. In a more detailed

analysis, it would be important to extend the analytical framework to consider the GHG emissions increases associated with the production and disposal phases.

In addition, the rebound effect, whereby the cost savings derived from replacing older products with more energy-efficient ones can actually induce an increase in energy use, is not considered since we were not confident that we could accurately determine how consumers would use their savings (e.g., they might use their air conditioners more than before or purchase other energy-consuming goods). Access to such information would allow for more precise modeling.

3. Results

As mentioned in Section 2.1, this study specifically addressed household air conditioners manufactured in the years 1995–1999 that were replaced by purchases made during the years 2005–2013. Table 1 presents results for the three estimated parameters (α_0, α_1, and α_2) of the dynamic discrete choice model for cases in which the value of the discount factor, β, is 0 (Model 1) and 0.9 (Model 2), respectively. All three parameters were estimated at a significance level of 1% in both models (Table 1). We conducted a likelihood ratio test using the log-likelihood shown in Table 1 for testing the null hypothesis $\beta = 0$. The test shows that the null hypothesis was rejected at a significance level of 1%, which implies that the dynamic discrete choice model with a discount factor β that is not zero is statistically supported.

The solid lines in Fig. 1 represent the replacement rates in the baseline case estimated by the parameters in the dynamic discrete choice model with $\beta = 0.9$ (Model 2 in Table 1). This baseline represents the results for the case in which the Home Appliance Eco-Point Program is adopted.

According to Fig. 1, in 2009, the first year in which the Home Appliance Eco-Point Program was implemented, the replacement rates of air conditioners produced from 1995 through 1999 were 15.1% (1995), 14.4% (1996), 13.9% (1997), 13.7% (1998), and 13.1% (1999). In 2010, the respective replacement rates were 17.5%, 18.6%, 19%, 19.1%, and 19.3%.

Table 1
Estimation results of the dynamic discrete choice model.

Parameter	Model 1 ($\beta = 0$)	Model 2 ($\beta = 0.9$)
α_0 (intercept term)	−3.091***	−3.745***
	(0.064)	(0.177)
α_1 (avoidable electricity cost)	−0.028***	−0.016***
	(0.002)	(0.001)
α_2 (net price of a new air conditioner)	−0.507***	−0.577***
	(0.004)	(0.016)
Log-likelihood	−15096	−14991
N	6445	6445

Bootstrap standard error in parentheses.
*** Statistically significant at the 1% level.

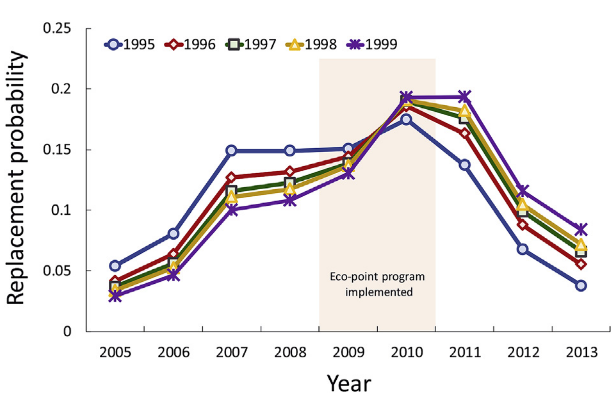

Fig. 1. Replacement rates of air conditioners for each production year with the eco-point program.

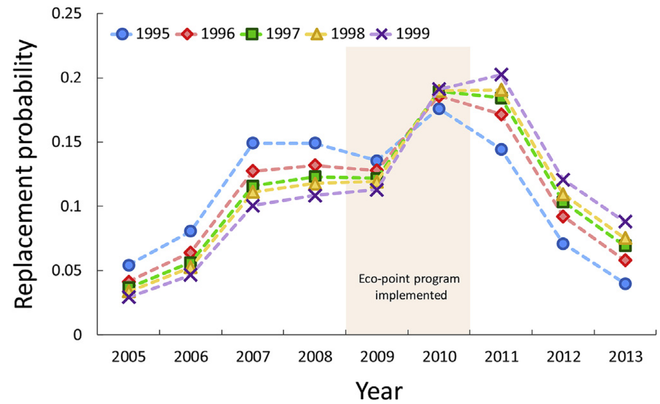

Fig. 2. Replacement probabilities of air conditioners for each production year in the case that the eco-point program had not been conducted.

The dotted lines in Fig. 2 indicate the replacement rates for each air conditioner production year for the case in which there is no Home Appliance Eco-Point Program in 2009 or 2010, using the parameters in the dynamic discrete choice model with $\beta = 0.9$ (Table 1). These replacement rates were estimated by re-estimating the replacement rates with the monetary value of the eco-points, p_t^{ep}, set to zero in the $u_{i,t}^k = \alpha_0 + \alpha_1(e_{i,t} - e_t^{new})p_t^e$ part of the utility function in Eq. (1). As shown in Fig. 2, the replacement rates in 2009 for model years 1995 through 1999 were respectively 13.5%, 12.8%, 12.2%, 11.9%, and 11.3%; the rates in 2010 were respectively 17.6%, 18.5%, 18.9%, 19.0%, and 19.1%.

The extent to which the Home Appliance Eco-Point Program contributed to increasing the replacement rates in 2009 and 2010 can be established by comparing the replacement rates in 2009 and 2010 *with* the Home Appliance Eco-Point Program (Fig. 1) and *without* the program (Fig. 2). We first see that the 2009 "replacement stimulus effect" (i.e., $\Delta\tilde{P}_{i,t} = \tilde{P}_{i,t}^{With} - \tilde{P}_{i,t}^{Without}$) for production years 1995 through 1999 was, for the respective production years, 1.5%, 1.6%, 1.7%, 1.8%, and 1.9%. In 2010, the replacement stimulus effects were respectively −0.1%, −0.01%, 0.06%, 0.1%, and 0.2%. The 2010 results show that the Home Appliance Eco-Point Program had virtually no impact on increasing the replacement rate for that year. This may well have been due to the substantially lower number of per-replacement eco-points awarded to consumers in 2010. Additionally, the large number of replacements in 2009 is likely to have reduced the number of replacements that would otherwise have been made in 2010.

Our 2009 results showed that the replacement stimulus effects for 1998 and 1999 air conditioners (1.8% and 1.9%, respectively) were higher than those for units produced in 1995 and 1996 (1.5% and 1.6%, respectively). (In checking the statistical significance of the differences in the replacement stimulus effects using an appropriate *t*-test, we confirmed that these differences were statistically significant.) A possible reason for this is that household air conditioners produced in 1998 and 1999 had been used for a shorter time than those produced in 1995 and 1996. Thus, in 2009, when the Home Appliance Eco-Point Program was first implemented, in-use household air conditioners that were produced in 1998 and 1999 were more numerous than those produced in 1995 and 1996.

Table 2
Effects of the Home Appliance Eco-point Program on GHG emissions during 2005–2013 (unit: tCO_2eq).

Eco-point use effect	Electricity use decrease effect	Total
7985	−36501	−28516

Table 2 shows the estimated influence of the Home Appliance Eco-Point Program on GHG emissions based on the Japanese Input–Output table (2011) and embodied GHG emission coefficients from Nansai (2018). Table 2 shows that although the *eco-point use effect* increased GHG emissions by 7985 tCO_2eq, the *electricity use decrease effect* was −36,501 tCO_2eq, indicating that the Home Appliance Eco-Point Program brought about a net reduction of 28,516 tCO_2eq in cumulative GHG emissions.

The results in Table 2 show that the Home Appliance Eco-Point Program had a clear GHG emissions reduction effect. It is important from a program design viewpoint to estimate the additional reduction effect that could be expected from changing the number of the eco-points awarded. Fig. 3 shows the GHG emissions reduction and cost per ton of CO_2eq GHG reduction as a function of the number the eco-points granted. The vertical axes at the right and left of Fig. 3 show, respectively, the GHG reduction amount and the cost per ton of CO_2eq GHG reduction. The horizontal axis shows the rate of change of eco-points when eco-points of the baseline (i.e., $p^{ep}_{2009} = 10,000, p^{ep}_{2010} = 4,000$) are set to 100%. Fig. 3 indicates that if the number of eco-points is increased from the baseline, additional GHG emission reduction effects can be expected. As shown, the maximum GHG emission reduction effects are obtained when the number of eco-points is approximately 2.3 times the baseline and the amount of GHG emission reduction is 41,803 tCO_2eq. However, the emission reduction effects begin to decrease beyond this peak. One possible reason is that the additional GHG emissions increase produced by the *eco-point use effect* is greater than the additional GHG emission reduction generated by the *electricity use decrease effect*.

It is important, from an environmental policy perspective, to analyze whether the GHG emission reduction effects produced under the program are sufficient to justify the cost of the program. To conduct the appropriate analysis, we converted the estimated eco-points issued by the Home Appliance Eco-Point Program to households that replaced their air conditioners into monetary terms based on the consumer price index of 2010. The total estimated value is approximately 24.5 billion JPY. As described above, the program produced a net reduction in GHG emissions due to air conditioner replacement of 28,516 tCO_2eq. Based on these values, the cost per ton of CO_2eq GHG emission reduction is 85,861 JPY (= 24.5 billion JPY/28,516 tCO_2eq). Converted to US dollars using the yearly average 2010 exchange rate taken from the International Financial Statistics published by the International Monetary Fund (IMF), this reduction cost corresponds to roughly 978 USD per ton. Comparing this reduction cost to the reduction costs of other replacement programs estimated in previous studies (Li et al., 2013; Davis et al., 2014), we found that the reduction cost of the Home Appliance Eco-Point Program is substantially greater (92–288 USD per ton according to Li et al. (2013) and 547 USD per ton according to Davis et al. (2014)). Furthermore, increasing the number of eco-points awarded to consumers will only increase the reduction cost per ton (see Fig. 3). For household air conditioners targeted in this study, although a reduction in GHG emissions was realized, the Home Appliance Eco-Point Program proves to be unattractive from a cost-effectiveness perspective.

4. Discussion and conclusion

Results show that, for the household air conditioners targeted in the study, the Home Appliance Eco-Point Program is not a cost-effective approach to reducing GHG emissions. For a Home Appliance Eco-Point Program to achieve meaningful cost-effectiveness, greater GHG emissions reduction needs to be accomplished with fewer eco-points. Visually, this means shifting upward and to the left the peak of the GHG emission reduction curve shown in Fig. 3. Measures to achieve this are discussed below.

Two factors play a key role in determining the effectiveness (cost-effectiveness) of product replacement programs such as the Home Appliance Eco-Point Program: (1) the improvement in energy efficiency obtained by replacing older products with newer ones, and (2) the elasticity of product replacement demand relative to the rewards offered by the program. With regard to the first factor, we compared the energy efficiencies of air conditioners produced from 1995 through 1999 with those produced during 2009 and 2010 based on the annual electricity consumption of 2.8 kW class household air conditioners as shown in the energy-saving performance catalog issued by the Agency for Natural Resources and Energy of Japan (2010 through 2014). In so doing, we determined that the average improvement rate in annual electricity consumption is approximately 30%. Although this level is not low by any means, it proves to be insufficient from a cost-

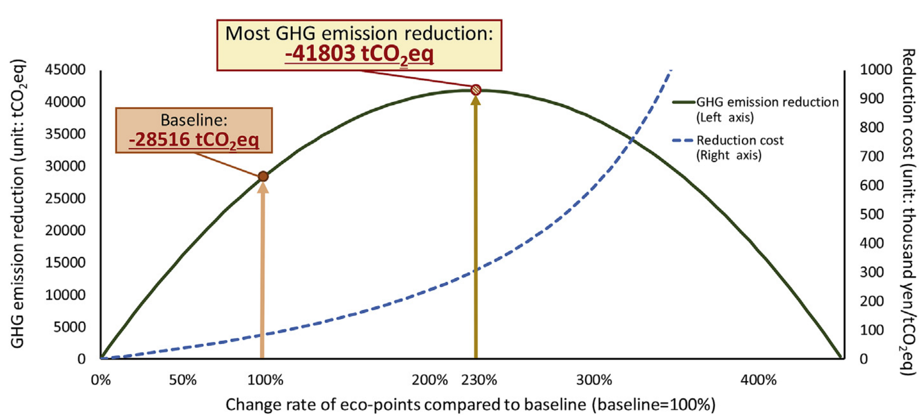

Fig. 3. GHG emission reduction and reduction cost for the number of eco-points.

effectiveness viewpoint. The improvement rate in the annual electricity consumption of household air conditioners in Japan has tended to decrease gradually year by year. In recent years particularly, annual electricity consumption has remained relatively stable and any marked reduction in electricity consumption has proved to be difficult (Agency for Natural Resources and Energy of Japan, 2010 through 2017). As a consequence, even if replacing older products with new energy-efficient products is incentivized through a product replacement program like the Home Appliance Eco-Point Program in the future, the reduction in annual electricity consumption per unit will almost certainly be lower than it was in 2009 and 2010, when the Home Appliance Eco-Point Program was in effect. If the program is reintroduced unchanged, it is likely to become increasingly inefficient from a cost-effectiveness standpoint. One idea that may improve program efficiency is to prioritize much older products for replacement, since the improvement in energy efficiency that can be achieved with product replacement is generally greater for older products.

As noted above, the second factor influencing the cost-effectiveness of a product replacement program intended to achieve a reduction in GHG emissions is the elasticity of product replacement demand relative to the rewards offered by the replacement program. With the Home Appliance Eco-Point Program, replacement by highly energy-efficient products was encouraged by offering eco-points as an offset to replacement expenses. In terms of the previously cited barriers to energy efficiency identified by Sorrell et al. (2004), the Home Appliance Eco-Point Program might be considered a countermeasure to the “access to capital” barrier that limits the introduction of energy-saving products because of insufficient capital for the initial investment. In this study, although the Home Appliance Eco-Point Program increased replacement rates by 1.5%–1.9% in 2009, these increased rates are insufficient from a cost-effectiveness viewpoint given the high GHG reduction cost. Moreover, our results show that an increase in the number of home electronics eco-points comes with an increased reduction cost (see Fig. 3), suggesting that we should not expect any additional improvement in cost-effectiveness by increasing the size of the eco-point awards. Thus, for the household air conditioners targeted in this study, there is a clear limit to the extent to which we can lower the “access to capital” barrier through the Home Appliance Eco-Point Program. Accordingly, attention should be paid to some of the other barriers to energy efficiency.

One of the barriers deserving of attention is the barrier of “imperfect information” (Sorrell et al., 2004), whereby consumers underestimate the energy-saving effects due to a shortage of information and/or a failure to recognize of the true energy-saving effects of the new product. Because consumers may not fully appreciate the benefits derived from the reduction of operating costs resulting from reductions in electricity consumption, programs like the Home Appliance Eco-Point Program may not have as dramatic an effect as they otherwise might. In terms of the dynamic discrete choice model used in the current study, this corresponds to the value of α_1, which relates to annual operating cost, not being sufficiently large (in the minus direction). If consumers were made more aware of the benefits of improving energy-related performance, the effects of a product replacement program might well be improved. For example, devices such as smart meters and HEMS have been introduced in recent years, enabling homeowners to check their home's electricity consumption status at any time. If consumers are able to more clearly see the effects of using energy-saving home appliances through such devices, their response to opportunities to improve energy efficiency can be expected to grow (i.e., the negative value of α_1 will increase). Accordingly, the performance of replacement programs like the Home Appliance Eco-Point Program will be elevated. In addition, using such devices to generate accurate information related to electricity consumption on a routine basis can serve as a countermeasure to the “bounded rationality” barrier to energy efficiency, whereby the purchase of energy-saving products is deterred by time-related limitations (Sorrell et al., 2004). Lowering this barrier should contribute to the increased effectiveness of programs such as the Home Appliance Eco-Point Program.

In this case study, we focused on the impact of the Home Appliance Eco-Point Program in Japan with respect to household air conditioners. We examined quantitatively the effect of the program on the consumer's decision regarding the time of replacement, the GHG emission reduction effect of the program, and the program's cost-effectiveness. Results indicate that although the Home Appliance Eco-Point Program brought about a reduction in GHG emissions, the program is an inefficient environmental measure from the viewpoint of cost-effectiveness. Consumer durables replacement programs have been introduced into many countries as a means to reduce environmental loads by promoting replacement of older products with new energy-efficient products through subsidies and/or rebates. While real reductions in environmental loads can be realized through such programs, it is important, from a cost-effectiveness perspective, that we consider the extent to which energy efficiency will be improved through replacement and the extent to which increases in product replacements can be expected due to the replacement program. If these are insufficient, the reduction in environmental loads will fall short of justifying the program's cost. To support the effectiveness of product replacement programs as components of environmental policy, appropriate coordination that includes not only replacement programs but also other polices related to consumer durables will be needed.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.02.220.

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